Understanding in-field soil moisture variability and its effect on irrigation, Project 10-2020 Final Report

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Background and Objectives

There have been many studies to estimate soil moisture, particularly as it relates to irrigation. However, due to the heterogeneity of soils and the variability of vegetation and, in some areas, topography, soil moisture can vary over time and space, making it a challenge to estimate. Not surprisingly, studies have shown that the variability in soil moisture increases with decreasing average moisture content and vice versa. One study suggested that vegetative characteristics could be indicative of soil moisture, particularly under dry and intermediate soil moisture conditions. The drier the soil, the more variability, and this suggests that more sampling points are needed to characterize soil moisture under drier conditions. In addition, many studies have looked at soil moisture levels near the soil surface (~0-4 in), but when making an irrigation decision, it is important to estimate the soil moisture in the active rooting zone of the plant. Another study evaluated soil moisture in the crop rooting zone but only recorded nine soil moisture measurements throughout the growing season. Soil moisture sensors have been shown to conserve water without reducing soybean yields by applying irrigation when the plant needs it and removing some of the guesswork from irrigation scheduling. In addition, granular matrix sensors (GMS) are most commonly used in Mississippi to help schedule irrigation applications. However, questions remain on how many sets of sensors are needed for a given area. This project will help determine if the in-field variability is enough to warrant a higher density of sensors and a different irrigation schedule for different areas of a field. Specific objectives will 1) measure in-field spatial and temporal variability of soil moisture in the active rooting zone of soybeans; 2) evaluate the correlation of root zone soil moisture to soil texture, elevation/slope, and crop variables; 3) use a crop model to determine if in-field soil moisture variability is great enough to indicate a different irrigation schedule for different areas of the field; and 4) share results with producers.

Report of Progress/Activity

Summary of Objectives 1 and 2

Site-specific irrigation decisions require information about variations in soil moisture within the rooting depth actively being used by the crop. Producers have been using soil moisture sensors to make irrigation decisions, and it has been shown that soil moisture sensors can reduce water use without reducing yields. There are still unanswered questions on improving efficiency with soil moisture sensors based on density and location of sensors within a field. This three-year study used sensors to evaluate the spatiotemporal variability of soil moisture across an 18-ha production field in a corn/soybean rotation. A 55 m by 55 m grid was laid on the field, which resulted in 44 sampling points that fell either underneath the center-pivot irrigation or the end gun. At each point location, two Watermark granular matrix sensors were installed at depths of 31, and 61 cm for 2018 and 2020 and an additional 76-cm sensor in 2019. Analysis of soil samples collected in year one of the project revealed fairly homogeneous soils across the field with silty clay loam as the major soil type and only eight percent silt loam. Plant height and leaf area index (LAI) were measured weekly at each of the 44 sampling points. Inverse distance weighted (IDW) interpolation methods were used to predict soil water tension (SWT) values for locations between the known points and aid in sensor density and placement within the field. Linear regression was used to model the relationship of LAI and plant height with soil matric potential to find surrogate methods for predicting SWT.

Conclusions from Objectives 1 and 2

The results analyzing the relationship of LAI and plant height to measured SWT show that vegetative variables alone cannot be used to predict soil moisture variability. When there are high amounts of rainfall and irrigation during the peak LAI and plant height, there is a negative relationship between SWT and plant height and SWT and LAI, although the relationships still have similar absolute values. Even with a homogenous soil type, there is considerable soil moisture variability. This could be due in part to variation in soils by depth within each grid cell. While soil cores for textural analysis were taken to a depth of 61 cm, textural analysis was not done at individual depth-specific layers. In addition, soil moisture was measured to a depth of 76 cm in 2019 when corn was grown in the crop rotation. The primary source of variability can be likely be attributed to the topography of the field and the six-meter difference in elevation over the field, causing water to move to the low-lying areas.

Even when evaluating soil moisture through the crop's active rooting zone, soil moisture variability is highest when the soil is driest as others have also found. Although there is variability in SWT between the measured point locations, each set of sensors responded to all irrigation and rainfall events that were more than 5 mm. There was also a similar pattern of drying as the field dried out each time, with the western side of the field that is lower in elevation drying out slower than the rest of the field. The east-central part of the field dried out more slowly, while the middle of the field generally dried out faster, possibly due to elevation differences.

When comparing the sampling schemes, it appears that the density of the sensors is not as important as the placement of sensors within the field if uniform irrigation applications are made. In this field with uniform irrigation applications, placing sensors based on elevation would be the best scheme to use. So, the four point locations in Figure 1 would be the best locations for the producer to use in this field. The elevation scheme does perform better than the gridded scheme with only four sensor sets in terms of predicting the soil moisture over the whole field, and if it is used, the same irrigation decision would be made as the full gridded field. If variable rate irrigation (VRI) is used, more sensors in a denser pattern may be needed to define management zones. Since the general drying pattern holds true for the field all three growing seasons (Figure 2), a producer could use a higher density of sensors for one to three years on a field by field basis to determine the drying patterns of each field. Then, after the pattern is identified, management zones can be created, and a more economical approach of fewer sensors can be used for either VRI or uniform applications.

Summary of Objective 3

There are multiple methods being used for scheduling irrigation applications that range from weather-based to ground-based methods. Growers must choose a method that is ideally both accurate and economical to use in a production agriculture system. One method that has been used is model based scheduling. For this objective, the CROPGRO-Soybean model in the Decision Support System for Agrotechnology Transfer (DSSAT) was used to evaluate soil moisture variability across a production soybean field. Also, 44 sensor sets were placed across the field on a 55- x 55-meter grid at depths of 31 and 61 cm, so that model predictions could be compared to measured data. Results showed that the model accurately predicted plant height and LAI in 2018 and 2020, with 2020 having the better results. Also, the model predicted soil moisture for 2018 well, but not as well for 2020. In both seasons, the model underpredicted soil moisture and occasionally did not respond to irrigation or rainfall the same way the sensors did. Even though the model underpredicted soil moisture, it predicted fewer irrigation events in 2018 than were actually applied (Figures 3 & 4) and similar irrigation events in 2020 (Figures 5 & 6). In 2018, one irrigation event was simulated, while seven irrigation applications were actually made. In 2020, there were four simulated irrigation events but only two actual irrigation applications, and less water was applied than the DSSAT model recommended.

Conclusions from Objective 3

Overall, the CROPGRO-Soybean crop model predicts the crop variables (LAI and plant height) well for both years, with plant height having the best results in terms of nRMSE and d stat in 2018. Plant height also had a better R^2 value and a slope closer to one. The model did not over predict or under predict the plant variables and had d statistics above the acceptable value, but LAI had a low R^2 and only 11 of 44 grid cells with acceptable d stats in 2018. In 2020, plant height had the best model results again, but LAI predictions were better in 2020 than in 2018, so the agreement of the model predictions with measured data for the two variables was very good in 2020. All of the grid cells in 2020 had very high d statistics (>.92), and the majority of the grid cell locations showed excellent and good ratings in terms of nRMSE. The R^2 values for both soybean variables were very high along with a similar slope in the regression equation close to one.

In 2018, the model did an adequate job of predicting soil moisture at the 31-cm depth based on the d stat of the grid cells. There were 36 of 44 cells with a d stat > 0.6 and nRMSE values less than 20%, so all of the grid cells were classified as excellent and good. At the depth of 61 cm, the nRMSE was still considered excellent for one grid cell and good for the other 43 grid cells, but the d stats were all < 0.6. At both depths in 2018, all of the grid cells are in the excellent or good range for nRMSE, but the 31-cm depth has more grid cells in the excellent range (25 vs 1). The data also show that the 31-cm depth has a slope closer to one (0.36 vs 0.06) with a higher R^2 value and are lined up more along the 1:1 line than data at the 61-cm depth. The model underpredicts the soil moisture at the 61-cm depth during the early part of the 2018 growing season.

For the 2020 season, the model does not predict soil moisture as well, with very low d stats and high nRMSE values at both depths. There were 14 and 24 grid cells classified as fair for comparisons at depths of 31 and 61 cm, respectively. The remaining grid cells have an nRMSE value > 30%, which is considered poor. The model performed slightly better in predicting soil moisture at the 61-cm depth more so than the 31-cm depth in 2020, but overall, the results were not adequate in terms of the d statistic. The 31-cm depth only had 1 grid cell out of 44 with an acceptable d statistic > 0.6, and the 61-cm depth only had 8 grid cells with a d statistic above 0.6. The DSSAT model underpredicts the soil moisture for both sensor depths in 2020, and the model does not react to rainfall or irrigation events at either depth late in the season. The soil moisture temporal patterns for most of the year are modeled similar to the actual measured temporal patterns, but the model underpredicts the soil moisture throughout the 2020 growing season. Even though the soil moisture predictions agree better with the measured soil moisture content in 2018 more so than in 2020, the irrigation predictions were more similar in 2020. This indicates that the producer may have overirrigated in 2018 (Figures 3-6).

The results from this project are valuable in advancing the application of DSSAT for estimating soybean vegetative characteristics and soil moisture variability. The use of models like DSSAT are an important tool for estimating the benefits of variable rate applications. The continued improvement of models is critical, particularly for capturing the variability of soil moisture over large areas, as accurate model-based soil moisture estimates have the potential for saving time and cost over the collection of soil moisture data using sensors. The DSSAT model is ideal for examining results from various hypothetical trials that could be conducted in the field. Crop simulation models can complement soil moisture sensors and provide a robust system that can used as real-time decision-making tools.

Impacts and Benefits to Mississippi Soybean Producers

Results from this project affect all soybean producers who are irrigating and using soil moisture sensors by showing the best placement of sensors within the field. Results show the importance of considering all variables that affect soil moisture, including elevation, so that sensors are located within the field to make the most accurate irrigation decisions and consequently, reduce water use and energy consumption. The results from this project are currently being used to develop a prescription application for variable rate irrigation (VRI) for this field, to use as an example for adopting sector control VRI on other fields under center pivot irrigation.

End Products – Completed and Forthcoming

Extension Products

1. Tagert, M.L. Sensors: It All Starts with Installation. *Irrigation Today*. Issue 2, Fall 2019. Pp. 6-7. http://www.modernpubsonline.com/0A406ys/ITFall2019/html/index.html?page=8&origin=reader

2. Video: How to Assemble and Properly Install Granular Matrix Soil Moisture Sensors. With Michaela Parker as videographer. https://youtu.be/vzIZCs3g6ac Developed July/Aug. 2019. The video received a 2020 Educational Aids Blue Ribbon award from ASABE and is posted on the Soybean Research and Information Network web site and on YouTube.

3. Understanding In-Field Soil Moisture Variability and Its Effect on Irrigation. M.L. Tagert, B. Hodges, J.O. Paz, and Q. Meng. Mississippi Soybean Promotion Board Research Round-Up. Dec. 9, 2020. Mississippi State University, Starkville, MS. (Virtual) Co-presented by M.L. Tagert and B. Hodges. (*29 participants)* Presentation was recorded and posted on the Mississippi Soybean Promotion Board YouTube page at https://www.youtube.com/watch?v=ZOXXrlCrxTA&t=34s.

4. North Mississippi Producer Advisory Council Meeting. Presented poster 'Evaluating In-Field Soil Moisture Variability and Factors Affecting It' authored by B.C. Hodges, M.L. Tagert, J.O. Paz, and D.B. Reginelli. Verona, MS. Feb. 20, 2020. (*42 participants*)

5. North Mississippi Producer Advisory Council. Feb. 21, 2019. Verona, MS. Presented poster titled 'Use of Sensors to Measure In-Field Soil Moisture Variability' authored by B. Hodges, M.L. Tagert, J.O. Paz, and D. Reginelli.

6. An Extension publication is being processed to share project results.

Thesis

Blade Hodges. Understanding In-Field Soil Moisture Variability and Associated Impact on Irrigation. November 2020. Blade accepted a job with Helena Agri-Enterprises, LLC as an AgrIntelligence Area Technician in January 2021 and covers the areas of Lake Providence, Tallulah, and Mer Rouge, Louisiana.

Student Awards related to project

- Blade Hodges, M.S. Student

- One of two statewide recipients awarded a $1,500 scholarship sponsored by the Mississippi Chapter of the Air and Waste Management Association.
- Awarded a USDA Southern SARE Graduate Student Grant for project 'Factors Affecting In-Field Soil Moisture Variability and its Effect on Irrigation' for $10,845; 09/01/19-08/31/20
- 1st Place, Community Engagement Research in Physical Sciences and Engineering. Mississippi State University Spring Undergraduate Research Symposium. Starkville, MS. April 16, 2019.

Peer-Reviewed Papers[*]

1. Hodges, B., M.L. Tagert, and J.O. Paz. A Modeling Approach Using DSSAT to Evaluate In-Field Soil Moisture Variability in Irrigated Soybean. *Irrigation Science*. Submitted Jan. 2021 and currently undergoing revisions.
2. Hodges, B., M.L. Tagert, J.O. Paz, and Q. Meng. Assessing In-Field Soil Moisture Variability in the Active Root Zone. *Precision Agriculture*. Submitted Dec. 2020 and currently undergoing revisions.

* Note: Full copies of the papers will be shared when they are published.

Scientific Conference Presentations

1. Hodges, B, J.O. Paz, M.L. Tagert, Q. Meng. 2020. Assessing in-Field Soil Moisture Variability Using the Decision Support System for Agrotechnology Transfer (DSSAT) Model. 2020 ASA-CSSA-SSSA international Annual Meeting. (oral presentation; virtual meeting)
2. B.C. Hodges, M.L. Tagert, J.O. Paz, and Q. Meng. A geospatial analysis of in-field soil moisture. 2020 ASABE Virtual Annual International Meeting. July 12-15. (oral presentation)
3. M.L. Tagert, B. Hodges, J.O. Paz, and D. Reginelli. Using Soil Moisture Sensors to Understand In-Field Soil Moisture Variability. 2019 ASABE Annual International Meeting. Boston, MA. July 7-10. (Oral presentation no. 1901508) (*36 participants)*
4. B. Hodges, **M.L. Tagert**, J.O. Paz, and D. Reginelli. Factors Affecting In-Field Soil Moisture. 2019 Mississippi Water Resources Conference. Organized by Mississippi Department of Environmental Quality, Mississippi Water Resources Research Institute, and U.S. Geological Survey. Hilton Jackson; Jackson, MS. April 2-3, 2019. (oral presentation)
5. B. Hodges, **M.L. Tagert**, J.O. Paz, and D. Reginelli. Evaluating In-Field Soil Moisture Variability with Sensors. Spring 2019 Undergraduate Research Symposium. Colvard Student Untion, Mississippi State Univ. April 16, 2019. *Undergraduate Researcher advised by* ***Dr. M.L. Tagert****.* (poster presentation) Awarded 1st Place, Community Engagement Research in Physical Sciences and Engineering.
6. B. Hodges. Understanding In-Field Soil Moisture Variability. Summer 2018 Undergraduate Research Symposium. Griffis Hall. Mississippi State, MS. Aug. 1, 2018. *Undergraduate Researcher advised by* ***Dr. M.L. Tagert****.* (poster presentation)

Graphs, Figures, and Tables

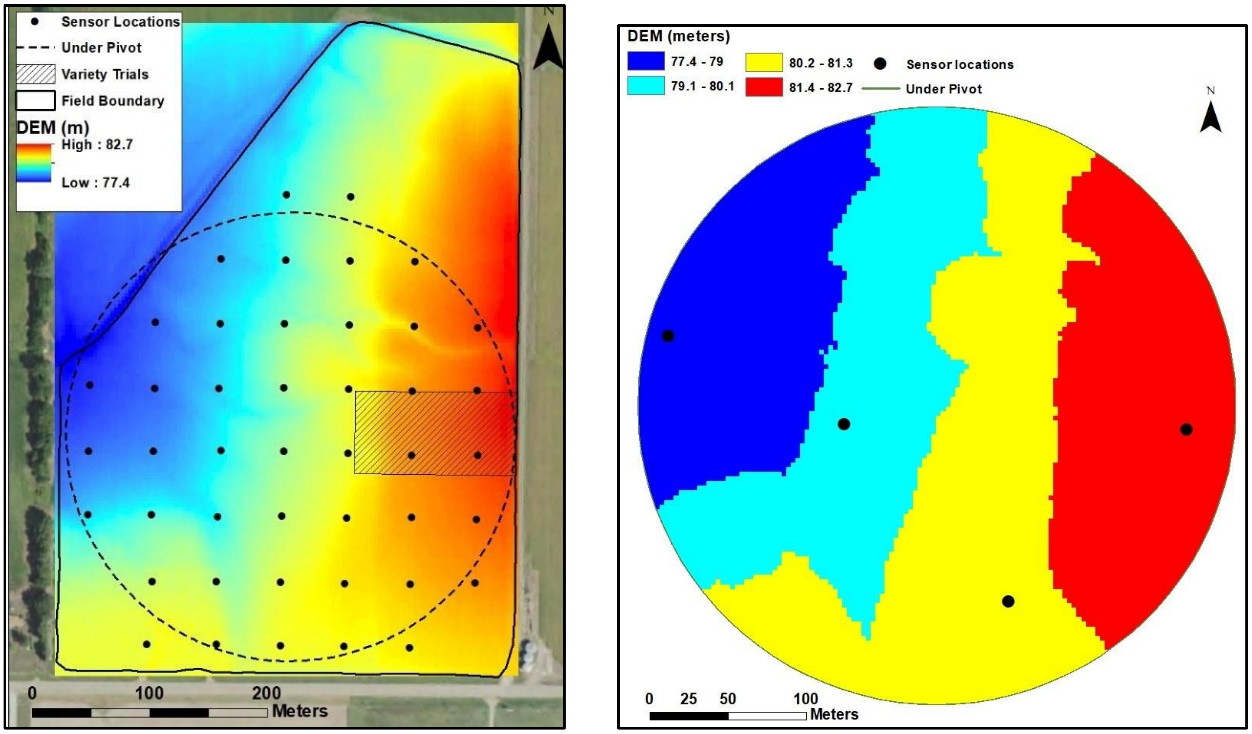

Figure 1. The elevation over the field (left) and the elevation-based sensor placement (right).

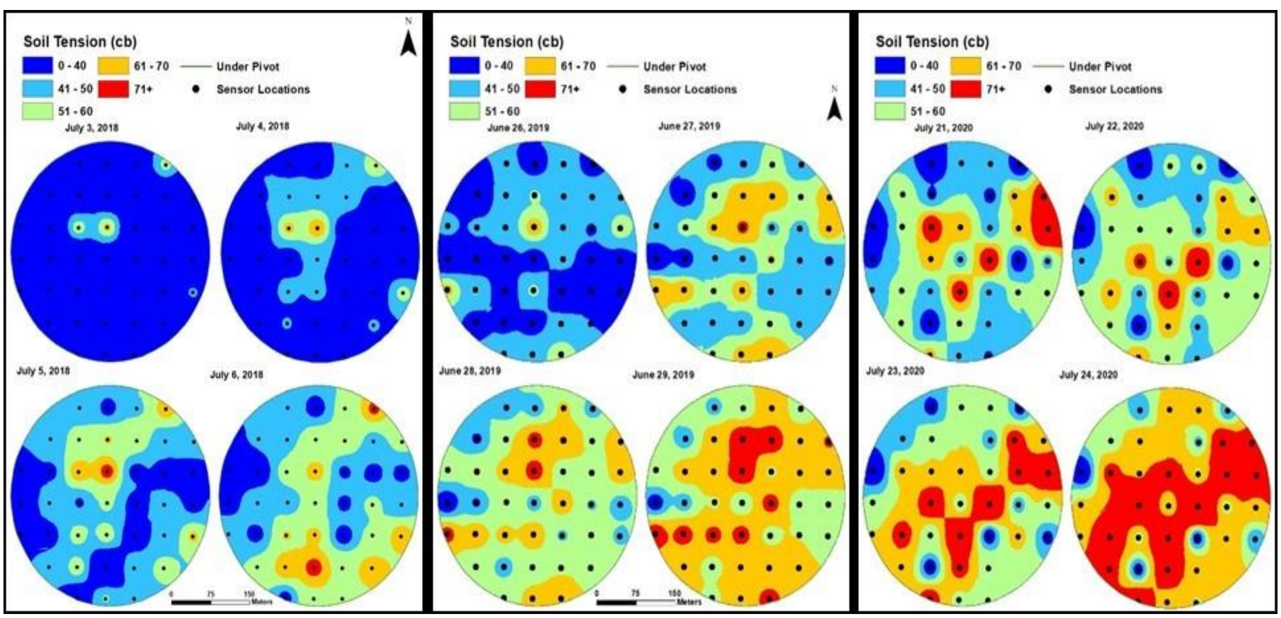

Figure 2. 2018, 2019, and 2020 soil tension progression for days leading up to an irrigation event.

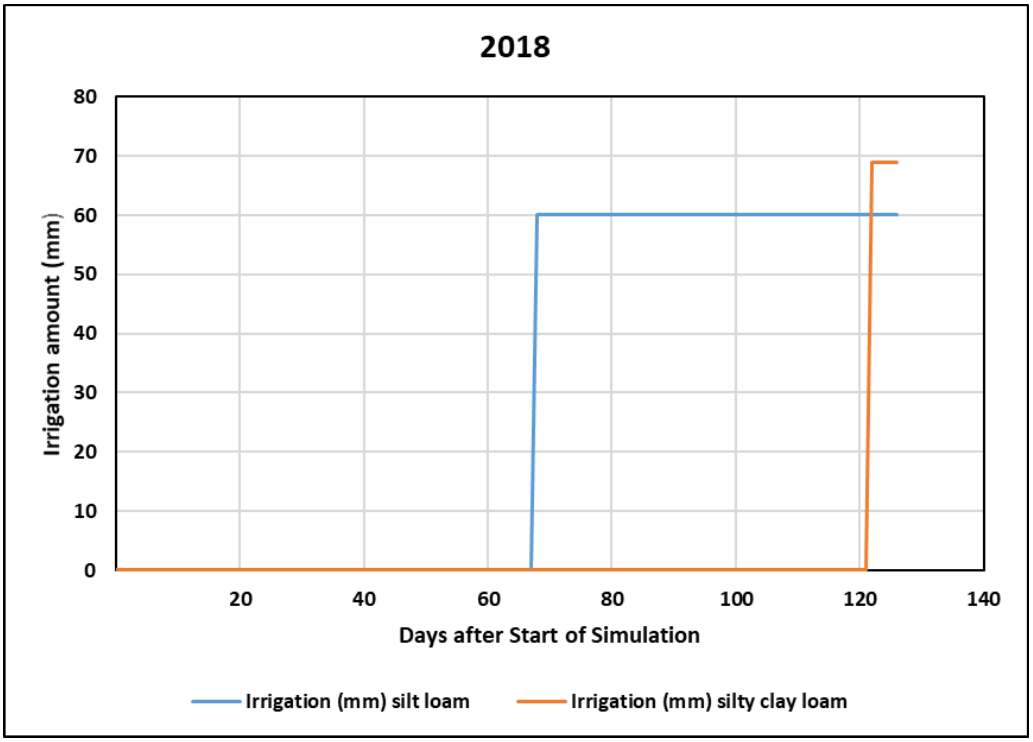

Figure 3. 2018 DSSAT-predicted irrigation events for both soil types in the field.

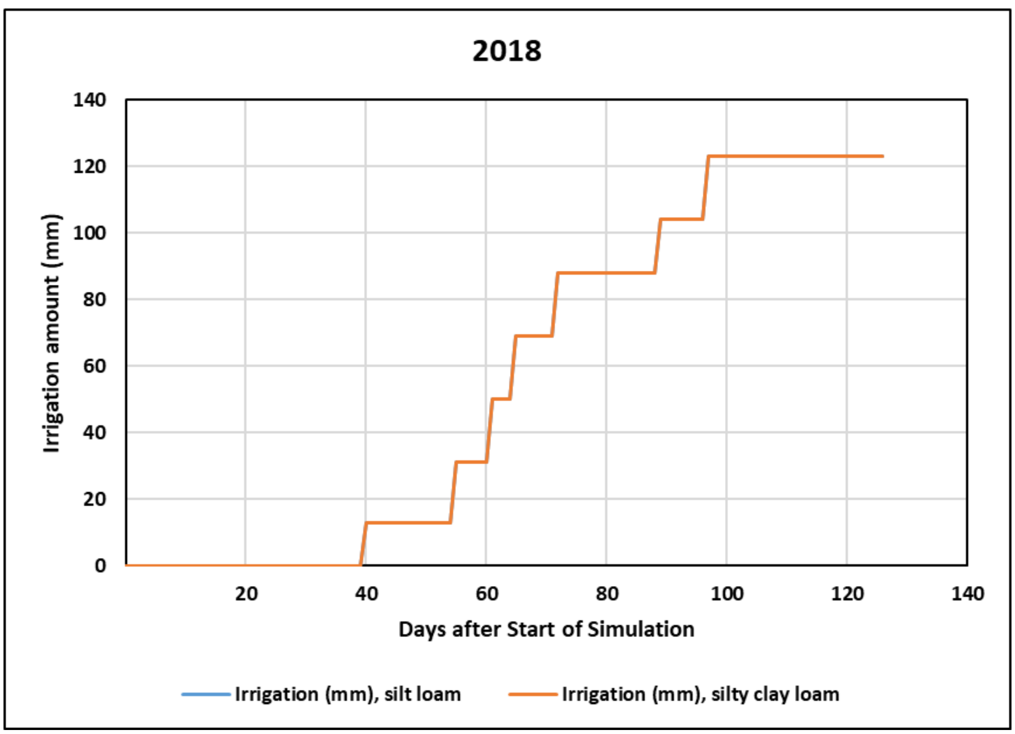

Figure 4. 2018 actual irrigation applications.

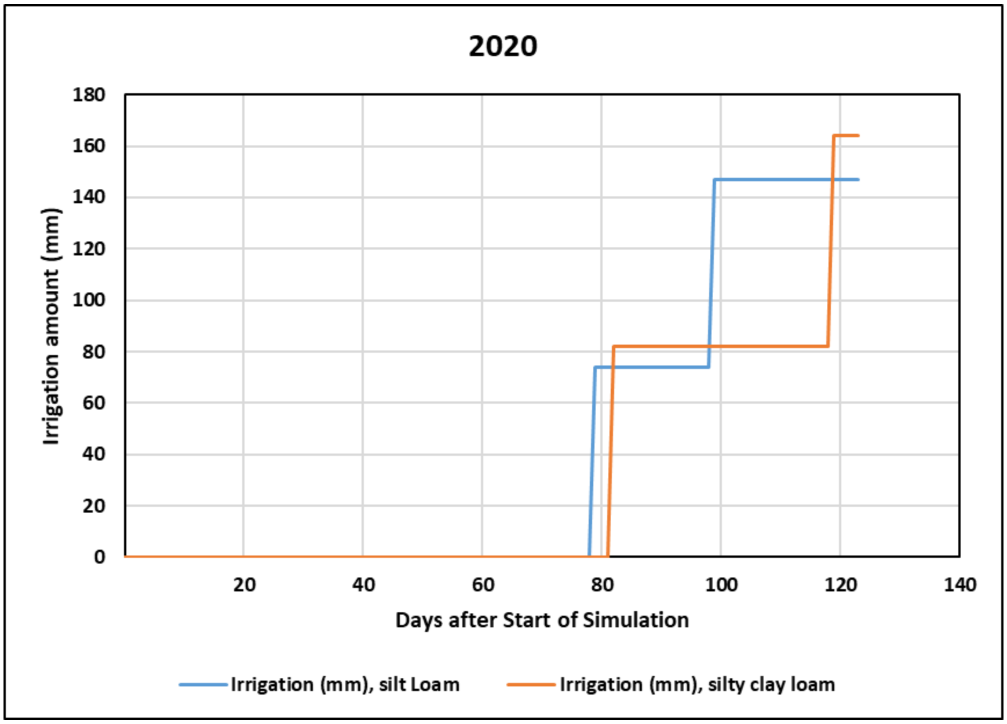

Figure 5. 2020 DSSAT-predicted irrigation events for both soil types in the field.

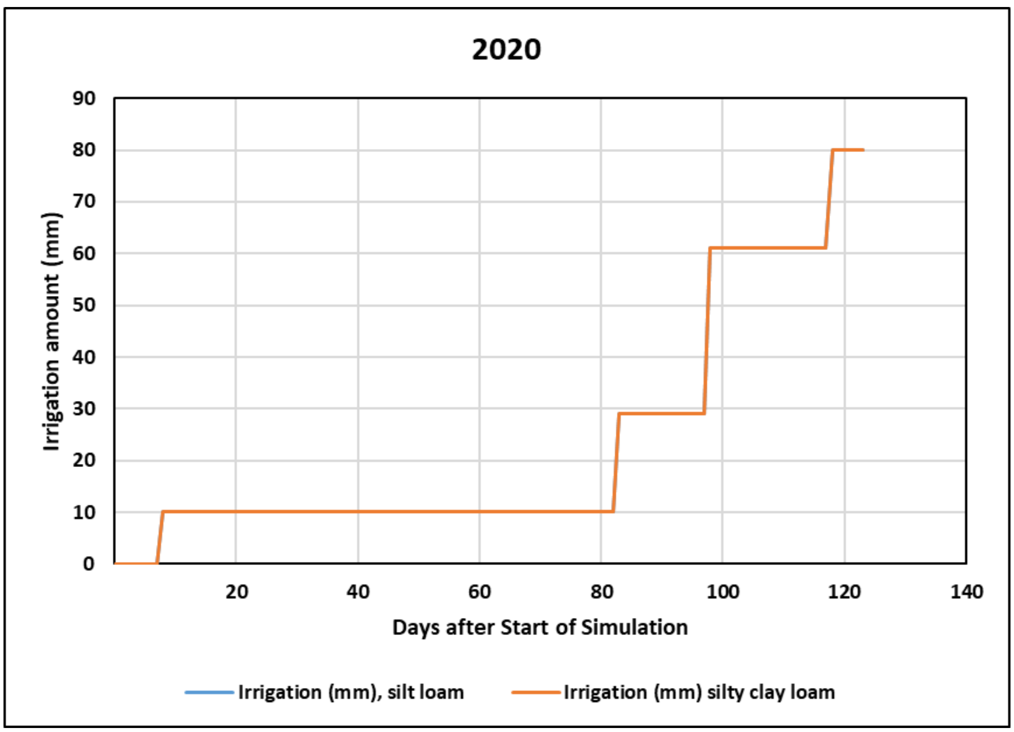

Figure 6. 2020 actual irrigation applications.